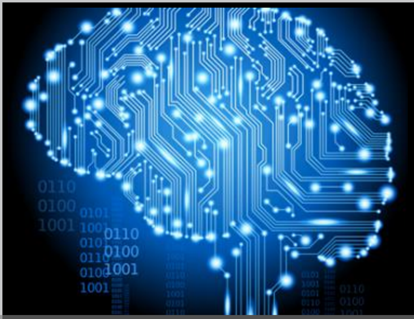
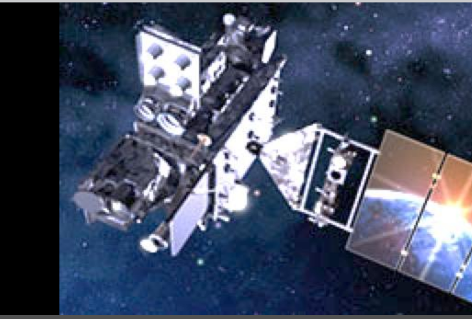




# A MACHINE LEARNING APPROACH TO LOW EARTH ORBIT SATELLITE HEALTH AND SAFETY TELEMETRY


Zhenping Li

ASRC Federal, 7000 Muirkirk Meadows Dr #100, Beltsville, MD 20705


Image credit: Japan Meteorological Agency

## Introduction

The machine learning (ML) approach includes

- An architecture model that defines the machine learning processes and interfaces.
- A scalable and extensible enterprise architecture for a ML system that provides common infrastructure and services for ML algorithms that are treated as mission specific software components
  - implemented in Advanced Intelligent Monitor System (AIMS).
- A ML algorithm library that provides efficient and accurate data training outputs for telemetry data and instrument calibration data.

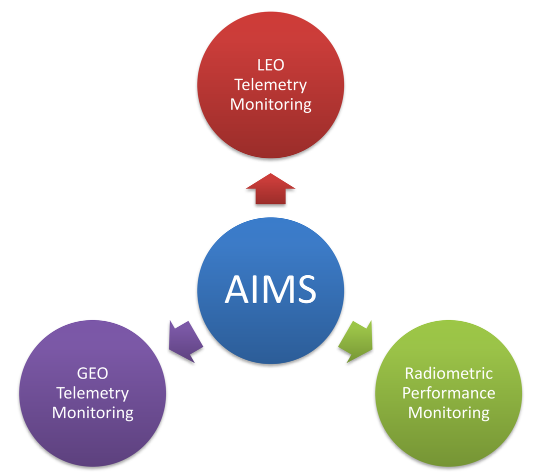



Figure 1: AIMS has been applied to GEO, LEO telemetry data monitoring and satellite instrument Radiometric performance monitoring

## Satellite Telemetry Data Challenges

- **The Separation of expected data pattern changes in normal operations from unexpected data pattern changes due to anomalies is essential.**
  - Not all data pattern changes in telemetry lead to anomalies, and they also be result of normal satellite operations or changes in space environments
  - Anomaly detections without the separations of expected from unexpected data pattern changes lead to false positives

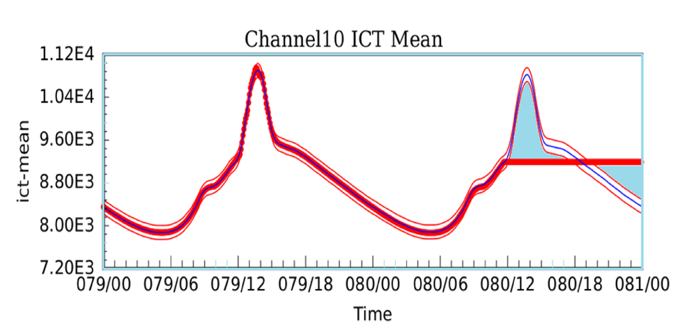



Figure 2 An anomaly example in an instrument radiometric data. The thick red line represents the actual data that became flat. The blue line and orange lines are ML model output and data bound.

- **Correlations among multiple telemetry datasets in multiple subsystems must be considered in separating normal operations from anomalies.**
  - Interactions among subsystems in a satellite lead to strong correlations among telemetry datasets.
  - Data pattern changes due to normal satellite operations or anomalies generally involves multiple telemetry datasets in multiple subsystems.

## A Hybrid Approach

**Detect data pattern changes through a supervised learning**

- Learning normal data pattern in datasets, while detecting data pattern changes.

**Separate anomalies from normal operations with an unsupervised learning**

- Define a quantitative metric that measures data pattern changes
- Develop a mathematical representation to characterize correlations among datasets
- Correlation patterns determine if data pattern changes are part of normal operations or anomalies

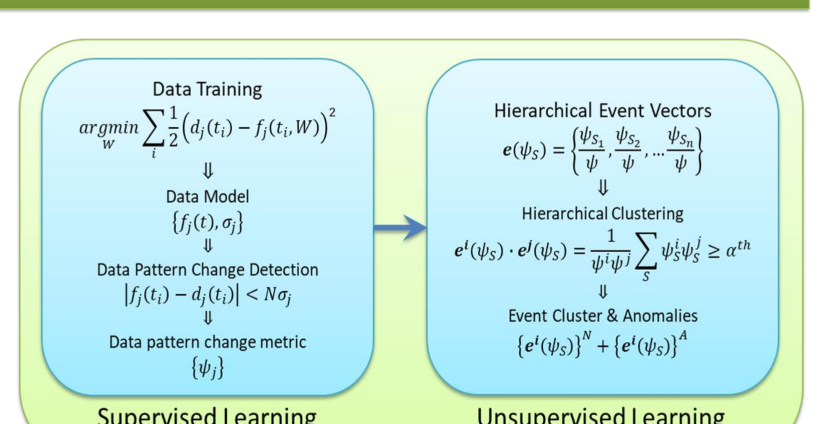



Figure 3 The hybrid approach to anomaly detections in satellite telemetry datasets.

## Data Training for LEO Satellite Telemetry Data

**The challenges in the data training of LEO satellite telemetry data**

- More diverse data types, High complexity in data patterns, and Relationships exists among datasets

**The requirements for data training in operational environments**

- Efficiency: data training for a dataset should be completed in seconds or minutes instead of hours or days.
- Accuracy: essential in detecting data pattern changes in datasets.
- Robustness: the training data may contain outliers that distort data training outcome

**The flexibility in selecting different data models for different patterns and noise level is critical**

Figure 4 The data training output for the current and voltage in the power system. The red dots are the actual data and blue lines are the data training outputs. The datasets, such as the one in the power subsystem or the satellite temperature profiles, have typical data patterns that follow the satellite orbital behavior with the same pattern period as the orbital period.

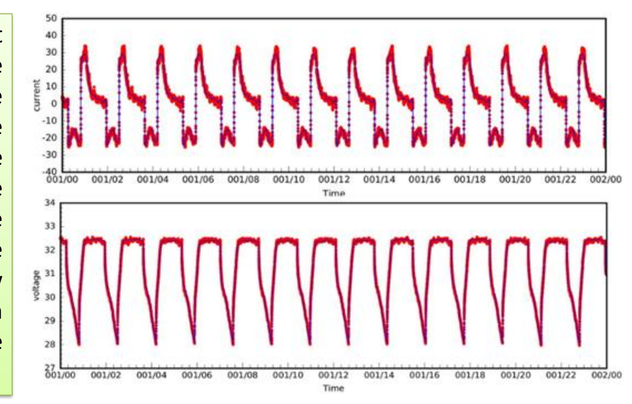


Figure 5 The data training output for the quaternions that determine the satellite attitude. The data patterns for the quaternions follows the satellite orbit period. The quaternions are generally not continuous. Neural networks are generally implemented as the data model for quaternions. Detecting data pattern changes in quaternion is critical in capture the signature of satellite maneuver.

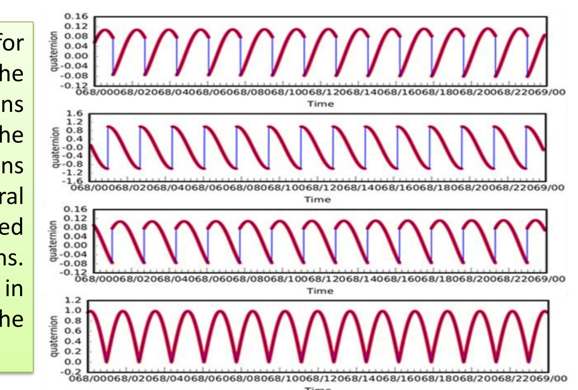


Figure 6 The data training output for the momentum profile of the reaction wheel. The red dots are the actual data and blue lines are the data training outputs. The data patterns of reaction wheel don't follow orbital patterns and highly complex. The Fourier expansion model is implemented.

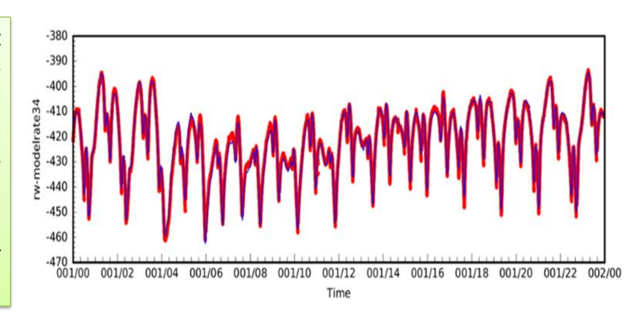
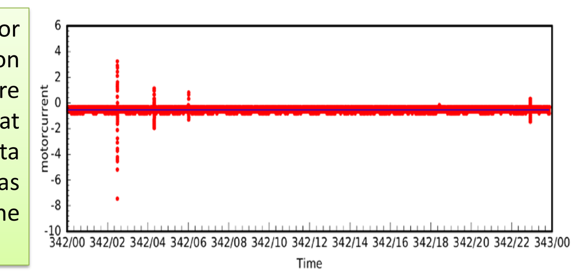


Figure 7 The data training output for the motor-current in the reaction wheel subsystem. There are significant number of datasets that are constant and noisy. The data points in vertical lines are treated as outliers that correlates with outliers in other datasets.



## The Quantitative Metric Measuring Data Pattern Changes

Data pattern change metric:

$$\psi_j = \frac{1}{T}\sum_i \frac{1}{2f_s}\left(\left|O_j^N(d(t_i))\right| + \left|O_j^N(d(t_{i-1}))\right|\right)\delta\left(t_i - t_{i-1} = {}^1/_{f_s}\right)$$

$O_j^N$ is the **normalized outlier** for a single data point:

$$O^N(d(t_i)) = \frac{\delta(|\Delta(t_i)| > N\sigma)}{N\sigma}\{\Delta(t_i) - sign(\Delta(t_i)) \cdot N\sigma\}$$

where

$$\Delta(t_i) = f(t_i, \{S_k\}) - d(t_i)$$

Normalized outlier is a dimensionless quantity so that different telemetry data points can compare with each other.

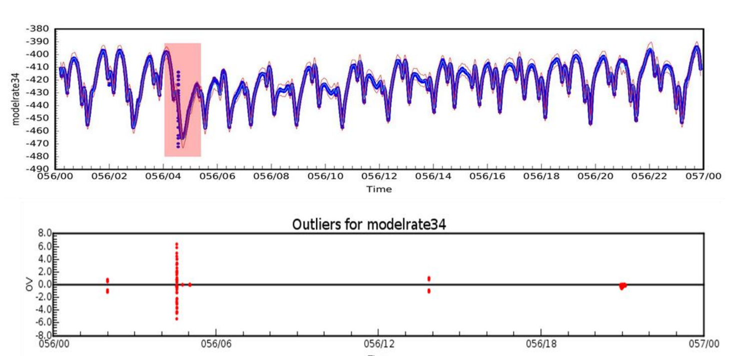



Figure 9 The outliers in the reaction wheel momentum profile (left) are converted into normalized outliers (right). The normalized outlier plots are used to highlight correlations among telemetry datasets.

## The Event Vector

Both normal operations and anomalies can be regarded as events. Events are characterized by event vectors consisting of the metrics $\psi_i$ for data pattern changes occurred in the same time period

$$\boldsymbol{e}(t_i, t_f) = \left\{\frac{\psi_1}{\psi}, \frac{\psi_2}{\psi}, \dots \frac{\psi_n}{\psi}\right\}$$

where $t_i, t_f$: start and time of an event

$$\psi = \sqrt{\sum_i \psi_i^2}$$

- Event vectors characterize correlations among telemetry datasets. Patterns in event vectors provides signatures of normal operations or anomalies
- Event vectors provide a mathematical representation in machine learning for event classifications and anomaly detections

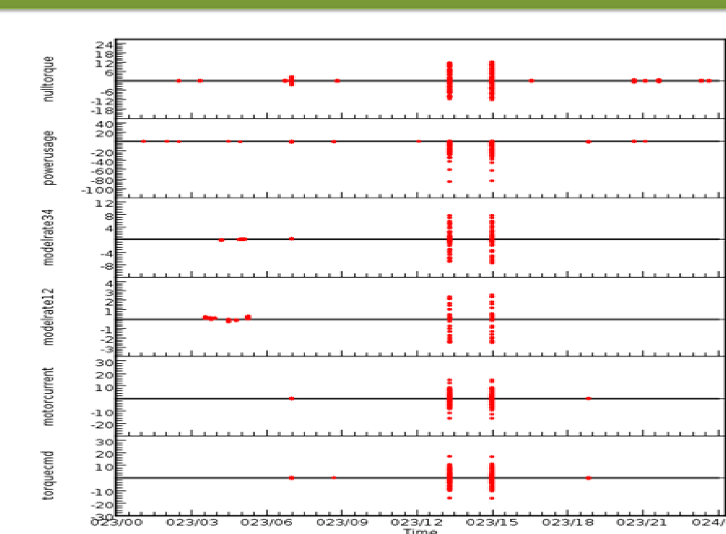


Figure 10 An example of two events with outliers aligned at the exact same time for multiple datasets in the reaction-wheel subsystem. The outlier plot provides insights into the correlations among datasets in multiple subsystems.

## Event Vectors Are Hierarchical

- A dataset can be defined by its physical hierarchical path: ***Subsystem/mnemonic/index***
- An event vector can be defined at subsystem level or mnemonic level by aggregation of event vectors at lower levels

$$\psi_S = \sqrt{\sum_M \psi_{S,M}^2}$$

and

$$\psi_{S,M} = \sqrt{\sum_I \psi_{S,M,I}^2}$$

- Event vectors at higher levels reduces the space dimensions while keeping sufficient information for event classification and anomaly detections
- Perform clustering at different subsystem and mnemonic level.

$$\boldsymbol{e}(t_i, t_f) = \begin{cases} \dfrac{\psi_{S_1}}{\psi} \begin{cases} \dfrac{\psi_{S_1,M_1}}{\psi} \begin{cases} \dfrac{\psi_{S_N,M_1,I_1}}{\psi} \\ \dots \\ \dfrac{\psi_{S_N,M_1,I_l}}{\psi} \end{cases} \\ \dots \\ \dfrac{\psi_{S_1,M_k}}{\psi} \begin{cases} \dfrac{\psi_{S_1,M_k,I_1}}{\psi} \\ \dots \\ \dfrac{\psi_{S_1,M_k,I_l}}{\psi} \end{cases} \end{cases} \\ \dots \\ \dfrac{\psi_{S_N}}{\psi} \begin{cases} \dfrac{\psi_{S_N,M_1}}{\psi} \begin{cases} \dfrac{\psi_{S_N,M_1,I_1}}{\psi} \\ \dots \\ \dfrac{\psi_{S_N,M_1,I_l}}{\psi} \end{cases} \\ \dots \\ \dfrac{\psi_{S_N,M_k}}{\psi} \begin{cases} \dfrac{\psi_{S_N,M_k,I_1}}{\psi} \\ \dots \\ \dfrac{\psi_{S_N,M_k,I_l}}{\psi} \end{cases} \end{cases} \end{cases}$$

## Hierarchical Event Clustering

Clustering Criteria: Two events belong to the same cluster if

$$\boldsymbol{e}^i(\psi_S) \cdot \boldsymbol{e}^j(\psi_S) = \frac{1}{\psi^i \psi^j}\sum_S \psi_S^i \psi_S^j \geq \alpha^{th}$$

- The value for $\boldsymbol{e}^i(\psi_S) \cdot \boldsymbol{e}^j(\psi_S)$ has the range from 0 to 1.
- The value of $\alpha^{th}$ is between 0.95 to 0.98.

The events as part of normal operations are generally repeatable and happen regularly, which form their own clusters.

The events corresponding to anomalies are generally not repeatable and happens rarely with their own characteristics, which are part of noise in event clustering.

**Hierarchical Clustering Algorithm**

***Perform clustering for all events at subsystem level***
*Output noise events*
*For each cluster at subsystem level*
*Perform clustering for events mnemonic level*
*Output noise events*

DBScan Clustering algorithm is implemented at each hierarchical level.

## Clustering Outputs for LEO Satellite Data

The outputs of the clustering of 354 events over 75 days of the Suomi National Polar-orbiting Partnership (NPP) satellite telemetry data includes

- The cluster dominated by the data pattern changes in star tracker subsystem and the cluster dominated by reaction wheel subsystems.
- Two orbit maneuver events.
- Two noise events are detected that are potential anomalies.

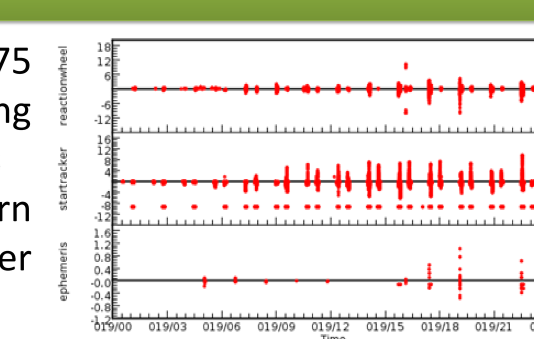


Figure 11 The signature of events as a part of the cluster dominated by data pattern changes in the star tracker subsystem..

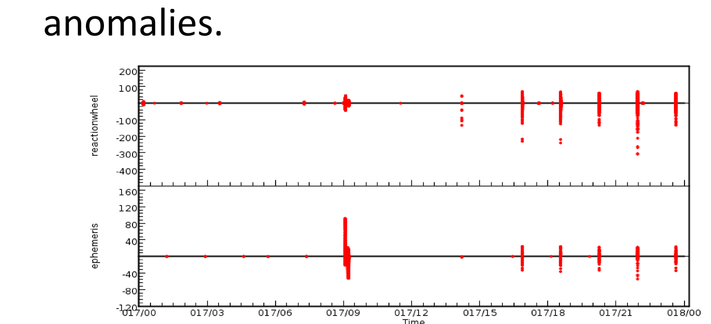


Figure 12 The signature of orbital maneuver event around 9:00z and events as a part of the cluster dominated by data pattern changes in the reaction wheel subsystem..

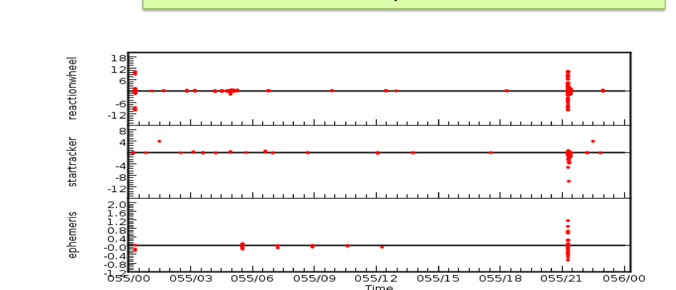


Figure 12 The signature of a noise event that is a potential anomaly.